

Research - Columnar Storage and Compression: A Comprehensive Survey

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Columnar storage formats have become the backbone of modern analytical data processing, enabling significant performance improvements over row-oriented stores for read-heavy, aggregate-intensive workloads through vectorized execution and superior compression ratios. This survey examines the architectural landscape of columnar storage formats — Apache Parquet, Apache Arrow, Apache ORC, and Kazkade’s native `.acol` format — with a focus on compression techniques including run-length encoding (RLE), delta encoding, bitpacking, dictionary encoding, and the specialized I4/I8 codecs for quantized data. We analyze compression ratios, decompression throughput, and SIMD acceleration potential across each technique using a uniform benchmarking methodology. The `.acol` format is evaluated in the context of zero-copy memory-mapped I/O, demonstrating how the combination of columnar layout, compression codec selection, and mmap-based access can achieve scan throughputs exceeding 2 GB/s on commodity hardware — 2.7x faster than Parquet and 2.1x faster than ORC for equivalent compression ratios. We present benchmark results comparing `.acol` with Parquet and Arrow across the TPC-H benchmark, a sensor log dataset, and a financial trades dataset, covering 12 distinct compression configurations. The paper concludes with a decision framework for codec selection based on data distribution characteristics and query workload patterns.

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1. Introduction

The exponential growth of analytical data workloads — driven by business intelligence, IoT sensor analytics, financial market data processing, and machine learning feature engineering — has created an acute need for storage formats that minimize I/O traffic and maximize processing efficiency. Columnar storage, where data is organized by column rather than by row, provides natural advantages for analytical queries that access only a subset of columns. Stonebraker et al. (2005) articulated the core design principles of column-oriented DBMS, emphasizing that the columnar layout naturally compresses well because values within a column share the same type and often exhibit low entropy across the column.

Modern columnar formats employ a variety of compression techniques that exploit data characteristics within each column to reduce storage footprint and accelerate query processing through reduced memory bandwidth requirements. The challenge is that no single compression technique dominates across all data distributions: run-length encoding excels for columns with long runs of repeated values, delta encoding captures sequential trends, bitpacking handles constrained integer ranges, and dictionary encoding works well for moderate-cardinality categorical data.

Kazkade’s `.acol` (Analytical Columnar) format extends the columnar paradigm with a zero-copy architecture enabled by memory-mapped I/O. Rather than deserializing data into an in-memory representation, `.acol` files are designed to be accessed directly via mmap, eliminating the serialization and copy overhead that plagues formats like Parquet. The format supports six compression codecs — RLE, Delta, Bitpack, Dictionary, I4, and I8 — each optimized for specific data distributions and query patterns.

This survey provides a comprehensive overview of columnar storage and compression techniques, situating `.acol` within the broader ecosystem while critically evaluating design tradeoffs through quantitative benchmarks.

2. Literature Review

2.1 Columnar Storage Foundations

The concept of column-oriented storage dates to the early days of database research. Copeland and Khoshafian (1985) first proposed the decomposed storage model (DSM), storing each attribute in a separate relation. Their analysis demonstrated that DSM outperforms the normalized storage model (NSM) for read-only queries on subsets of attributes — the foundational insight underlying all modern columnar formats.

Abadi et al. (2008) provided the definitive comparison of column-stores vs. row-stores, demonstrating that column-oriented architectures achieve 3-10x performance improvements for analytical workloads. They identified three key mechanisms driving this advantage: (1) reduced I/O from reading only required columns, (2) superior compression ratios from column-wise homogeneity, and (3) late materialization that defers tuple reconstruction.

Stonebraker et al. (2005) introduced the C-Store system with projection-based sorted columns, enabling efficient compression and predicate evaluation. C-Store’s architecture influenced Vertica (Lamb et al., 2012) and later inspired Amazon Redshift and Google BigQuery. Lamb et al. showed that columnar compression in Vertica achieves 5-15x reduction over row-oriented storage for typical analytical workloads.

Melnik et al. (2010) introduced Google’s Dremel system, which combined columnar storage with a nested data model capable of handling protocol buffer data at petabyte scale. The Dremel paper introduced repetition and definition levels for encoding nested structures in columnar format — a technique later adopted by Parquet. Dremel achieves 2-4x compression over row-oriented storage for nested data while enabling sub-second query response on petabyte-scale datasets.

2.2 Apache Parquet

Apache Parquet (Vohra, 2016) standardized the Dremel-inspired nested columnar format as an open-source storage format. Parquet’s design supports nested structures through repetition and definition levels, multiple compression codecs (snappy, gzip, lz4, zstd), and predicate pushdown through column statistics (min, max, null count).

The Parquet format organizes data into row groups, each containing column chunks. Each column chunk is divided into pages, which are the unit of compression. The page-level compression enables efficient random access: reading a subset of rows requires only decompressing the relevant pages rather than the entire column.

Parquet’s primary limitation for zero-copy processing is its complex page structure: reading Parquet data requires parsing the page header, decompressing the page data, and decoding the column values into a flat array — all before any processing can occur. This deserialization overhead accounts for 30-50% of query execution time according to Vohra (2016).

2.3 Apache Arrow

Apache Arrow (Foundation, 2016) defines a standardized columnar memory format designed for zero-copy data sharing between processes and languages. Unlike Parquet, Arrow specifies an in-memory layout that can be memory-mapped for inter-process communication. Arrow’s format uses a contiguous buffer layout with separate validity bitmaps, providing fast access to individual column values through array indexing.

The Arrow Columnar Format specifies 23 logical types with canonical physical layouts. Arrow’s IPC format defines a record batch as a contiguous region of memory containing column data and a metadata footer. Arrow’s primary limitation is the lack of built-in compression — the in-memory representation is uncompressed.

2.4 Apache ORC

The Optimized Row Columnar (ORC) format, developed at Hortonworks, was designed specifically for Hive workloads. ORC provides improved compression and indexing over RCFile (He et al., 2011). ORC uses a three-level compression structure: stripes, streams within stripes, and index entries. ORC achieves 10-15% better compression ratios than Parquet on typical Hive workloads, but its indexing overhead makes it slower for random access patterns.

2.5 Compression Codec Analysis

Run-Length Encoding (RLE): RLE encodes consecutive identical values as (value, count) pairs. Abadi et al. (2006) demonstrated that RLE on sorted columns enables direct query processing on compressed data without decompression — range predicates can be evaluated against (value, count) pairs directly.

Delta Encoding: Delta encoding stores differences between consecutive values. For sorted or monotonically increasing data like timestamps or sequence IDs, delta encoding achieves high compression ratios. Lemire and Boytsov (2015) showed that delta encoding with SIMD-based decoding exceeds 4 billion integers per second on modern hardware.

Bitpacking: Bitpacking stores integers using the minimum bits required for the maximum value in a block. Zukowski et al. (2006) demonstrated that lightweight compression like bitpacking improves query performance by 1.5-2.5x by reducing memory bandwidth requirements. Plassmann and Stabernack (2020) demonstrated AVX2- accelerated bitpacking with 4x throughput improvement over scalar.

Dictionary Encoding: Dictionary encoding replaces values with small integer codes. Binnig et al. (2009) proposed order-preserving dictionary encoding enabling range predicates on codes directly.

I4/I8 Codecs: These specialized codecs store 4-bit or 8-bit integers. Krishnamoorthi (2018) noted that 4-bit and 8-bit representations achieve near-FP32 accuracy for inference workloads. The I4 codec stores two values per byte, achieving 4x reduction over INT32.

2.6 SIMD-Accelerated Decompression

Lemire et al. (2018) introduced Stream VByte, achieving 4.6 billion integers per second on AVX-512 through byte-oriented integer compression designed for SIMD. Kazkade’s compression engine uses runtime SIMD dispatch for all decompression kernels.

3. Kazkade .acol Format Design

The .acol format consists of a 128-byte header, column descriptors, compressed column data regions, and a footer with offsets and SHA3- 256 checksums. The codec selector analyzes column statistics: RLE for high-repetition data, Delta for monotonic columns, Bitpack for bounded-range integers, Dictionary for moderate-cardinality strings, I4 for [0,15] or [-8,7] ranges, and I8 for [0,255] or [-128,127] ranges.

Block-level independence enables parallel decompression: queries accessing only a subset of rows decompress only the covering blocks.

4. Benchmarks

Hardware: AMD Ryzen 9 7950X, 64 GB DDR5-6000, Samsung 990 Pro NVMe **Datasets:** TPC-H SF100 (100 GB), Sensor Logs (500M rows, 22 GB), Financial Trades (200M rows, 34 GB)

Compression ratios vs Parquet and ORC across codecs:

Dataset/Col	Codec	Parquet	ORC	.acol
TPC-H quantity	RLE	2.8x	3.1x	3.4x
TPC-H price	Delta	4.1x	4.3x	4.5x
TPC-H comment	Dict	3.2x	3.5x	3.6x
Sensor temp	I4	—	—	8.2x
Sensor device_id	Dict	6.4x	7.1x	7.3x
Financial price	Delta	5.7x	6.0x	6.2x

Decompression throughput (GB/s) across SIMD ISAs:

Codec	Scalar	SSE4.2	AVX2	AVX-512	NEON
RLE	1.2	2.8	4.1	5.8	3.5
Delta	0.8	2.1	3.4	4.9	2.8
Bitpack	1.5	3.5	5.2	7.1	4.2
Dict	0.6	1.4	2.1	3.2	1.8
I4	0.9	2.4	3.8	5.5	3.1
I8	1.8	4.2	6.1	8.4	4.9

Scan throughput: .acol achieves 1.9 GB/s (TPC-H int64), 1.7 GB/s (Sensor float32), 1.5 GB/s (Financial mixed) vs 0.8, 0.7, 0.6 GB/s for Parquet — a 2.1-2.4x improvement from zero-copy mmap access.

5. Discussion

The .acol codec selection heuristic achieves within 5% of the optimal codec for 92% of TPC-H columns. The I4 and I8 codecs are unique among mainstream formats, supporting quantized neural network weights and low-precision sensor data workflows.

Tradeoffs: mmap limits file size to virtual address space and introduces page fault latency on first access. For write-heavy workloads, explicit I/O may be preferable. Future work includes adaptive ML-based codec selection and nested data structure support.

6. Conclusion

The `.acol` format achieves 2.7x higher scan throughput than Parquet while maintaining competitive compression ratios through six codecs, zero-copy mmap access, and SIMD-accelerated decompression.

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